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Original Research

Analysis of GPS and collision metrics during ball in play to identify positional key performance indicators and their prediction on game outcome in professional rugby union.

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Background and Aim

Ball in play (BiP) research in rugby is well defined, however literature is lacking where global position system (GPS) and collision data is considered. Therefore, the aim of the current study is to analyse GPS and collision data during BiP, identifying positional key performance indicators (KPI) and their prediction on the game outcome (points difference).

Method

BiP data of 54 professional rugby union players (height 185 ± 7 cm, weight 101 ± 11 kg, age 26 ± 4 years) from 25 games was analysed using a multiple linear regression for the full team and each positional group. Metrics observed to determine predicted significant effect on game outcome were collisions per min (COLL), accelerations events (ACC; ⩾2.5m/s^2), high-speed running (HSR; ⩾ 18 km/h), average speed in km/h (AVS) and metabolic power events (MPE).

Results

ACC in props (p =0.015), MPE in props (p =0.018) and fly half (p =0.040) and AVS in centres (p =0.046) showed significance regarding the prediction of the game outcome. The standardized β coefficient showed that HSR had the strongest influence predicting the game outcome for the scrum half (-0.809), hooker (-0.423), back three (-0.099) and the full team (-0.503). ACC showed to be strongest metric for props (-0.756), fly half (-0.668) and locks (STD -0.353) and MPE for centres (-0.335). Adjusted R^2 showed that back three (-0.190), locks (-0.133), loose forwards (-0.126) and hookers (-0.063) had no explanation regarding the model outcome.

Conclusion & practical implications

Elevated ACC in props had a negative effect on game outcome. Contextual factors within gameplay, such as opposition and possession, can affect ACC output. However, controlling and reducing ACC output is a strong predictor of match outcome and informs tactical strategy. These findings could help identify positional KPIs. Yet, the limitations of small sample size, coexisting variables, and study duration should be considered.

INTRODUCTION

Winning and losing in rugby union is often defined by small margins, and practitioners and coaches often refer to 1% gains.[1] These small margins are evident in Europe's professional leagues, where winning or losing is mostly defined by a difference of seven points.[2] Identifying key performance indicators (KPIs), whether they are tactical or physical in nature, which have a direct impact on a team or player's performance and ultimately leading to victory, is one of the key elements of sport specific analytics.[3] The position specific requirements and their influence on the game in professional rugby union have been the topic of many previous studies.[4-6] Physically rugby union players are expected to endure high physical contact events, such as tackling, rucking, mauling and scrummaging, accompanied with intermittent periods of high-intensity sprinting, jogging and low speed walking.[7]

Like other team sports, rugby union utilises GPS to quantify these external demands, providing sports scientists, coaches, and trainers detailed, real-time analysis of player performance during games or training.[8] As a tool to quantify external load GPS has shown to be reliable and valid.[9] GPS also has the ability to quantify collisions, due to its triaxial accelerometry technology. Other methods that can be utilised to quantify this data includes other micro technology units or expert video analyst coding, which are indicated to have greater reliability in rugby union.[10,11]

Problematic in the majority of studies, is the isolated view on performance measurements, ignoring coexistent and potentially influential factors.[12] Most notably, BiP, which is identified as one of the most influential parameters in the modern game of rugby union.[13] BiP describes the period between the referee's whistle to start a period of play and the whistle to end that specific period of play. As BiP in rugby union differs significantly from full game duration,[14-16] its performance measurement analysis, in contrast to research including the full game duration, results in different training recommendation and physical demands.[14] Similar can be seen in other sports such as Soccer,[17] Australian football[18] and Hurling.[19] The importance of this research can also be seen by the trend of increased BiP in rugby union over the past years and therefore the change in physical needs and appropriate training content.[15] A mean BiP time of 29 minutes per 80 minutes in international game time was recorded in 1992.[14] Over two decades later, in 2013 an increased time of 36:21 ± 2:40 minutes was measured.[16] Furthermore, an increased BiP time during Rugby World Cups of over 8 min from 1995 (25:45 minutes) to 2019 (34:21) has been noted.[13] This evolving increase of BiP underlines the demand for research including BiP and its relationship and effect on game influencing factors in rugby union. Further, to date there is a general void of BiP related research.[17-20]

Therefore, the aim of this study was to determine if collisions per min (COLL), accelerations events (ACC), high-speed running (HSR), average speed in kilometres per hour (AVS) and metabolic power events (MPE), predict game outcome (points difference (PD)) during BiP in professional club rugby. While other studies in rugby union which included BiP separated between "forwards" and "backs"[15,21] this study targeted to analyse each player group individually. Used analysis method aimed to identify if any of the chosen metrics had the potential of influencing player KPIs. Potentially influencing the physical preparation or tactical recommendations by sports performance practitioners and coaches.

METHODS AND MATERIALS

PARTICIPANTS

Fifty-four professional rugby union players (height 185 ± 7 cm, weight 101 ± 11 kg, age 26 ± 4 years) from one senior team, competing in the United Rugby Championship (URC) and European Rugby Challenge Cup (ERCC), were included and provided consent for data analysis and dissemination. Ethical approval was approved internally by the club, and agreement for the use and dissemination of data for publication agreed, meeting the Declaration of Helsinki (2018).

RESEARCH DESIGN

This study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines.[22] GPS, anthropometric and collision data collection was carried out by Benetton Treviso under the athletes consent as part of routine standard procedures for performance analysis.[11,23] Provided data was analysed as secondary data from this point on. Data was collected from 25 games of which 18 were played in the URC and five games were played in the ERCC of which four were group games and one a knockout game. URC and ERCC games have shown to have similar physical characteristics.[24] Furthermore, two preseason friendly matches were included in this analysis. All games took place between September 2021 and May 2022. Data was included if a player had played ⩾30 minutes of the total game time as shorter involvement potentially leads to higher outputs.[25] GPS data was collected with the GPEXE pro[2] 18 Hz GPS device (Exelio srl, Udine, Italy, firmware version 99). The GPS devices were placed, using a specialised vest, between the upper sides of the scapula blades to ensure optimal data collection.[26] As recommended by the manufacturer, devices were turned on 20 minutes prior to use for necessary satellite connection for data collection. Satellite visibility was excellent throughout the collection periods, with connection to 9.5 satellites and horizontal dilution of precision less than 1 (0.85) suggesting ideal positional signal.[27] The GPS devices employed in this study have recently been proven to be valid and reliable in identifying movement orientation in team sports[28] and further suitable for sprint acceleration force-velocity profiling.[29] The data collected during every game was downloaded via the Gpexe browser version as a XLXS file.

RESEARCH PROCEDURES

Five metrics; COLL, ACC, HSR, AVS and MPE in relation to BiP and their prediction on the game outcome (PD) were utilised. The chosen metrics offer coverage of the wide array of different physical demands and broad spectrum of factors influential for research regarding the game of rugby union.[15,30,31] HSR was defined by every meter that has been run with a speed of ⩾ 18 km/h. An acceleration event was recorded when >2.5m/s^2 was attained with a dwell time of ⩾ 0.25s. Average speed was collected as kilometres per hour. Regardless of the actual running speed, metabolic power events (MPE) are high intensity events in which a high anaerobic energy demand is created resulting in an oxygen debt which subsequently requires recovery time.[32] MPEs, in Watt per kg^{-1}, are calculated by the product of the energy cost and the velocity of the event.[33] In the first instance collision data was collected by two specialists via video analysis software (Hudl, SportsCode, version 12.4.8) followed by a review of collected data to ensure validity. Post-match analysis of the video data involved the extraction of player actions that included a collision: defensive and offensive rucks, tackles, carries, mauls, scrums and other events of collision. Results of this analysis for each game were noted in a XLXS file. Props, hookers and locks received a value of 1.0 collisions per scrum whereas loose forwards obtained 0.5 collisions per scrum this was due to their lower contribution to the total scrummaging force.[34] To classify game outcome, points difference from every game was calculated ranging from a negative 44 points to a positive 48 points (Mean: -5.8 ± 19.6). The positional classification in current literature uses player groups consisting of props, hooker, locks, loose forwards, scrum half, fly half, centres and back threes.[20,24]

The GPS, game outcome and collision data, according to their player groups, were combined in Microsoft Excel 2021. Microsoft Excel is extensively utilized and well-known, it serves as a robust tool for data storage and manipulation, functioning similarly to a database and facilitating the saving of data in various formats for dissemination among researchers and integration with specialized analytical software.[35] The created document included the GPS and collision metrics and their corresponding data for each game outcome of the 25 games. The data set of the full team (n=508) was distributed across the player groups; props (n=83), hooker (n=43), locks (n=69), loose forwards (n=96), scrum half (n=39), fly half (n=31), centres (n=62) and back three (n=85). The uneven distribution of the valid full team data on the different player groups is simply explained by that fact that some player groups permanently have two (props, locks and centres) or even three (loose forwards and back three) players of one group on the field. Whereas the remaining player groups (hooker, fly half and scrum half) only have one player of the group on the field at the same time. To generate equal datasets for each player group, equivalent to the number of games played (n=25), mean values of each metric for each group and game were computed. To generate a dataset of 25 for the full team, mean values of each group and metric of each game were calculated.

DATA AND STATISTICAL ANALYSIS

A multiple linear regression was carried out for each player group, and for the full team to predict game outcome (PD) from COLL, ACC, HSR, AVS and MPE. Regression equation:

$$Game\ outcome(points\ difference) = \beta_0 + \beta_1 \times COLL$$
$$+\beta_2 \times ACC + \beta_3 \times HSR + \beta_4 \times AVS + \beta_5 \times MPE + \in$$

The assumptions of linearity, independence of errors (Durbin Watson ranged between >1.0 and <3.0 for each player group), homoscedasticity, unusual points as assessed by studentised residuals not exceeding ±3, multicollinearity (VIF all < 9) and normality of residuals were met. JASP (JASP Team 2022, Version 0.16.3) was used for all data analysis with the level of significance being set at $p < 0.05$. Statistical significance was categorized into three levels of evidence against the null hypothesis ($p < 0.05$ = *, $p < 0.01$ = **, $p < 0.001$ = ***). A descriptive statistic was performed to determine mean value and standard deviation (SD) of each variable. The multiple linear regression further included the model summary consisting of adjusted R^2 and root mean square error (RMSE) of each metric and player group. While evaluated standardised β coefficients (STD β coef) and t-value were calculated as part of the coefficient analysis. These results targeted to reveal the individual strength and influence of each metric and player group on the dependent variable.

RESULTS

The variables ACC (p = 0.015, adj. R^2 = 0.262, STD β coef = -0.756) and MPE (p = 0.018, adj. R^2 = 0.262, STD β coef = 0.617) among the player group of props statistically significantly contributed to the prediction of the game outcome (PD). The negative t-value of ACC among props (-2.677) indicated that a higher number of ACC predict a negative game outcome (PD). While the positive t-value for MPE (2.586) implies that more MPE lead to a positive prediction of the game outcome (PD). MPE furthermore showed to be a significant predictor of the game outcome (PD) for the fly half (p = 0.040, adj. R^2 = 0.104, STD β coef = 0.861). Similar statement as with the props can be made for the fly half as the positive t-value for MPE (2.202) indicates that more of the events lead to a positive prediction of the game outcome (PD). The only other variable showing significant contribution towards the prediction of the game outcome (PD) was AVS among the centres (p = 0.046, adj. R^2 = 0.205, STD β coef = 0.639). Through the collected positive t-value (2.156) for AVS a higher average among the centres predicted a positive game outcome (PD). Hookers, locks, loose forwards, scrum half and back three showed no significance in any variable regarding the prediction of the model in any category.

When comparing the presented adjusted R^2 values in Table 1. with each other, the player groups consisting of hookers, locks, loose forwards and back three showed negative adjusted R^2 values. Hence, their explanation regarding the game outcome (PD) of the model is negligible, as there is an insignificance of the explanatory variables due to mentioned negative adjusted R^2 values. All other groups showed positive adjusted R^2 values and therefore their explanatory variables (COLL, ACC, MPE, HSR and AVS) have a percentual explanation on the dependent variable. Props showed the highest explanatory value with 26.2% followed by centres (20.5%), fly half (10.4%), scrum half (8.8%) and full team (7.5%). According to these results 65,9% of the variance can be explained through the measured values of the four player groups. When looking at RMSE there are no prominent outliers visible as the values range from 16.827 (props) to 21.363 (back three).

The presented standardised β coefficient of the variables in each player group serves to compare the strength of each of the five variables, independently of unit or scale and their individual effect on the game outcome (PD). Therefore, this enables a comparison of the relative importance of each coefficient for the model. For the Full Team HSR (STD β coef = -0.503) had the strongest effect on predicting game outcome (PD). This was also noted for the player groups of scrum half (STD β coef = -0.809), hooker (STD β coef = -0.423) and back three (STD β coef = -0.099). ACC showed the strongest effect in the player groups of props (STD β coef = -0.756), fly half (STD β coef = -0.668) and locks (STD β coef = -0.353). Only the player group centres showed MPE (STD β coef = -0.335) as their strongest vari-

Table 1. Multiple linear regression output for each player group and variable and their prediction on the game outcome (points difference PD).

		Full Team	Props	Hookers	Locks	Loose Forwards	Scrum Half	Fly Half	Centres	Back Three
Model Summary	**Adjusted R^2**	0.075	0.262	-0.063	-0.133	-0.126	0.088	0.104	0.205	-0.190
	[a]RSME	18.837	16.827	20.196	20.851	20.785	18.708	18.543	17.040	21.363
[b]COLL	**Mean (± [g]SD)**	1.24 ± 0.10	1.82 ± 0.30	2.02 ± 0.19	1.93 ± 0.24	1.73 ± 0.18	0.39 ± 0.12	0.67 ± 0.16	0.83 ± 0.19	0.52 ± 0.18
	[h]STD β coef	-0.271	0.161	0.015	0.037	-0.127	-0.147	-0.318	-0.242	-0.065
	t	-1.091	0.71	0.062	0.151	-0.474	-0.715	-1.514	-0.903	-0.220
	p	0.289	0.487	0.951	0.881	0.641	0.483	0.146	0.379	0.828
[c]ACC	**Mean (± SD)**	28.80 ± 5.49	13.78 ± 5.36	24.82 ± 9.94	15.76 ± 4.49	31.43 ± 6.51	27.88 ± 15.57	43.84 ± 12.62	37.26 ± 12.45	34.40 ± 6.72
	STD β coef	-0.207	-0.756	-0.056	-0.353	-0.204	0.196	-0.668	0.218	-0.096
	t	-0.690	-2.677	-0.156	-1.158	-0.658	0.494	-1.670	-0.586	-0.292
	p	0.499	0.015*	0.878	0.510	0.518	0.627	0.111	0.566	0.773
[d]MPE	**Mean (± SD)**	57.56 ± 9.43	40.40 ± 9.44	56.91 ± 14.37	54.40 ± 11.88	60.22 ± 11.91	57.30 ± 18.93	65.34 ± 17.70	67.29 ± 19.18	57.96 ± 9.76
	STD β coef	0.387	0.617	0.260	0.045	0.063	0.568	0.861	-0.335	0.178
	t	1.236	2.586	0.714	0.172	0.195	1.952	2.202	-0.604	0.530
	p	0.231	0.018*	0.484	0.865	0.847	0.066	0.040*	0.554	0.602
[e]HSR	**Mean (± SD)**	416.08 ± 80.10	138.18 ± 93.32	256.66 ± 92.54	174.59 ± 73.76	311.09 ± 85.62	523.19 ± 215.98	586.03 ± 158.31	653.80 ± 212.38	662.95 ± 166.56
	STD β coef	-0.503	0.143	-0.423	0.439	-0.062	-0.809	-0.300	-0.318	-0.099
	t	-1.528	0.462	-1.189	1.352	-0.17	-1.892	-0.957	-0.709	-0.285
	p	0.143	0.649	0.249	0.192	0.867	0.074	0.350	0.490	0.779
[f]AVS	**Mean (± SD)**	7.21 ± 0.41	6.62 ± 0.43	7.21 ± 0.51	6.73 ± 0.34	6.89 ± 0.42	8.17 ± 0.61	7.50 ± 0.52	7.66 ± 0.53	6.90 ± 0.55
	STD β coef	0.176	0.05	0.369	-0.101	0.249	0.311	-0.006	0.639	0.195
	t	0.569	0.244	1.447	-0.372	0.953	1.306	-0.024	2.156	0.726
	p	0.576	0.809	0.164	0.714	0.351	0.207	0.981	0.046*	0.477

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, [a]Root mean square error (RMSE), [b]Collisions per min (COLL), [c]Accelerations events ⩾2.5m/s^2 (ACC), [d]Metabolic power events (MPE), [e]High-speed running ⩾ 18 km/h (HSR), [f]Average speed in kilometre per hour (AVS), [g]Standard deviation (SD), [h] Standardised β coefficient (STD β coef) able. All results of the multiple linear regression can be seen in Table 1.

DISCUSSION

To the authors knowledge this is the first study investigating if GPS and collision metrics in specific player groups can be utilised to predict game outcome (PD) during BiP. The aim of this study was to analyse how selected GPS and collision metrics predicted the game outcome (PD) and if significantly, can be utilised to inform player KPIs.

Props were the stand-out player group overall as ACC and MPE showed high significance regarding the prediction of the game outcome (PD). The adjusted R^2 value among props was the highest of all player groups and the STD β coef of ACC had the strongest effect on the game outcome (PD). Therefore, highlighting reduced ACC output for props as a potential KPI, however the context of why these increased ACC were seen needs to be considered. A potential explanation for this finding could be defensive misplacements by props. This could result in an elevated amount of ACC and could, in a cascade of following events, lead to points being scored against. In addition, higher AVS among centres detailed significance in predicting game outcome (PD). This could be explained by a higher average speed, resulting in more distance being covered by the centres. Ultimately, leading to better tactical placement in both attack and defence. Another KPI identified for props and fly halves was MPE, as increases in this metric within both playing groups showed significance regarding the prediction of the game outcome (PD). MPE can emerge from various situations, such as physical contact or distance covered[36] thus further investigation in to this metric are required. In all instances listed, resultant KPI's identified should be evaluated in conjunction with the occurrence of the significant predictor variable via retrospective video analysis. This would provide vital information on whether it is of physical or tactical nature and guide the required coach intervention.

The present body of work has identified the potential for positional KPI development for periods of BiP. Emphasised by the results of all the three-way analysis, as the comparison between centres and fly half shows. For the centres the STD β coef value of AVS had the weakest effect of all metrics on the game outcome. Contrary to this the p-value for AVS was the only one that showed significance (p = 0.046) while the adjusted R^2 showed an explanatory value of 20,5%. For the fly half MPE had the weakest effect on the game outcome (PD) while the p-value showed to be significant (p = 0.040) in predicting the game outcome (PD). Finally, the adjusted R^2 value showed an explanatory value of 10,4%. Even though the fly half p-value for MPE was higher than the one recorded for AVS among centres adjusted R^2 in the player group fly half was close to less than half of the centres while the centres STD β coef indicated to have a higher effect on the game outcome (PD). Therefore, the results of the three-way analysis offer a more meaningful result for the centres. Quintessentially identifying that a higher average speed by centres conceivably had more potential of predicting a positive game outcome (PD) than additional MPE among the fly half. The creation of understandable output for end-users is vital for the success of any data collection and analysis.[27,37] The findings in this study showed the necessity to consider all the results of the completed analysis. Understanding these results and the relationships between metrics and their prediction towards the game outcome (PD), and with it success, can provide vital and purposeful in season feedback.[2]

Previous literature surrounding COLL presented by Pollard *et al.* and Couderc *et al.* presented a comparable mean value and SD within the player group of Backs, and a higher COLL values for the full team and Forwards.[15,38] These findings could be rationalised by the tactical play of the investigated team, which relied more on Forwards creating forward momentum, which ultimately results in increased COLL events. Contrastingly, Quarrie *et al.* details similarities regarding COLL outputs, and the distribution of HSR between player groups, as detailed in our work.[16] A comparison to other studies regarding AVS, ACC, MPE and HSR could not be found. This was due to either the non-inclusion of BiP or the different thresholds used for ACC, MPE and HSR. This issue regarding comparison due to different definitions and speed zones of inter and intra team sports research is a recognized, but not yet resolved issue and further work in this area is required.[23]

Limitations presented in this work included the small sample size, partly due to the investigation of a sole season, this is being underlined by presented negative adjusted R^2 values, an indicator for the lack of sample size. This further limited the option to complete inter competition analysis and comparisons between URC and ERCC. Due to the retrospective nature of this study, no practical in season implementation, intervention or recommendations were possible. However, findings can be utilised to inform future planning. To generate such in-season recommendation for physical preparation or adjustment continuous prospective analysis would be needed. To further increase the applicability of this model coexisting factors which have proven influence on the game, such as home advantage,[39] need to be included. In addition, through solely investigating the quantity of ACC, COLL and MPE without values, intensities or magnitudes caution regarding these results is warranted.

CONCLUSION

This study aimed to provide recommendations for future physical preparation and support regarding tactical decisions. For both physical preparation and tactical decisions potential KPIs were identified. These included the reduction of accelerations among props and higher average speed among centres. Importantly, results still required subjective interpretation and discussion, indicating the need for further work in this area. This would potentially inform coach and performance practitioner processes, highlighting the need for real time feedback. Theoretically influencing decision making regarding a player's or groups performance during games due to the prediction of a positive game outcome (PD). Future work should consider a larger sample size and longer study duration to build on the findings in this study.

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CONFLICT OF INTEREST

No conflict of interest reported.

AVAILABILITY OF DATA AND MATERIAL

N/A

AUTHORS' CONTRIBUTIONS

Kilian Bibby (KB), Alberto Botter (AB), Nicola Gatto (NG), Mathia Geromel (MG) & Jim Molony (JM), designed the manuscript of this study. KB, AB, and JM oversaw the correct use of methods and materials and result conclusion. AB, NG & MG advised on data extraction and statistical analysis. KB wrote the manuscript with critical input from AB and JM. All authors read and approved the final manuscript.

CONSENT FOR DISSEMINATION OF DATA AND PUBLICATION

Benetton Treviso Rugby declares that data has been approved for dissemination into publication.

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